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Computer-Aided Design of Nanomaterials with the Desired Bioactivity and Safety Profiles

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St Jude Children Research Hospital, USA

Outline: From data to models to computer-aided design



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1. Data Accumulation: Need to establish an integrated database of nanomaterials' structure and properties

2. Data modeling and nano-informatics: Need to develop new descriptors for nanomaterials

3. Application of the Quantitative Structure Activity Relationships (QSAR) approach to modeling of nanomaterials

4. Proof-of-concept: Computer aided design of carbon nanotubes with the desired bioactivity and safety profiles

- ~1000 manufacturer-identified nanotechnology-based consumer products currently on the market

(Woodrow Wilson International Center for Scholars, 2008).

Recent boost due in part to the application of **combinatorial chemistry and high throughput screening** to design novel Manufactured NanoParticles (**MNPs**)

- Growing public concern about the safety of MNPs since it has been demonstrated that **MNPs intended for industrial applications could cause toxic effects in humans.**

Myllynen, P. Nat. Nanotechnol., 2009, 4, 795-796.

Kippen et al. Am J Physiol Lung Cell Mol Physiol, 2005, 289, 696-697.

Experimental, toxicological testing of MNPs is costly and time-consuming and could thus restrict the development of newly designed particles.



Development of predictive « *in silico* » approaches

Main questions yet to be solved

Which MNPs are the most toxic?

What are the three most meaningful assays to determine MNP-induced toxicological effects?

What effects are already known for this class of particles?

Compared to this given organic chemical, is a particular MNP more or less toxic at the same dose?

Which nanomaterials to be tested first?

Are there correlations between the properties of MNPs and their characteristics?

At what dose do most MNPs start to be inducing toxic effects?

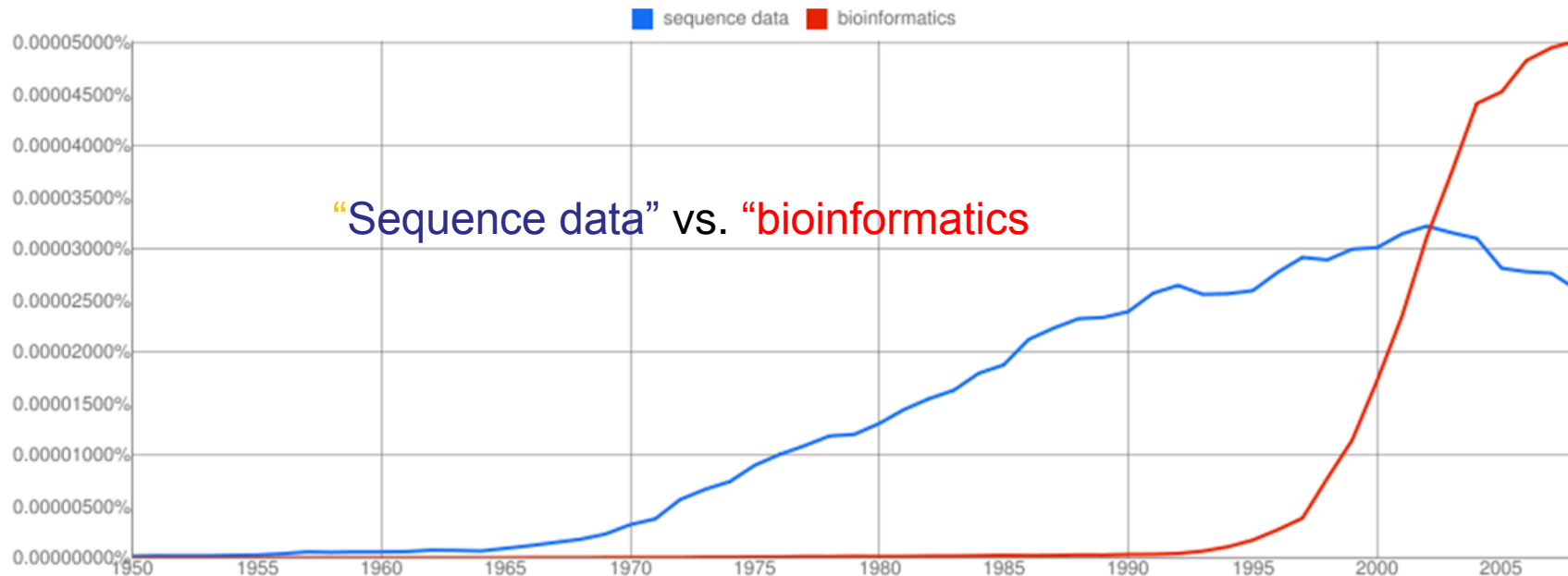
BUT WHERE ARE THE DATA?

The importance of the DATA to enable any informatics-dependent discipline: *bioinformatics example*



Google labs Books Ngram Viewer

Graph these **case-sensitive** comma-separated phrases:
between and from the corpus with smoothing of



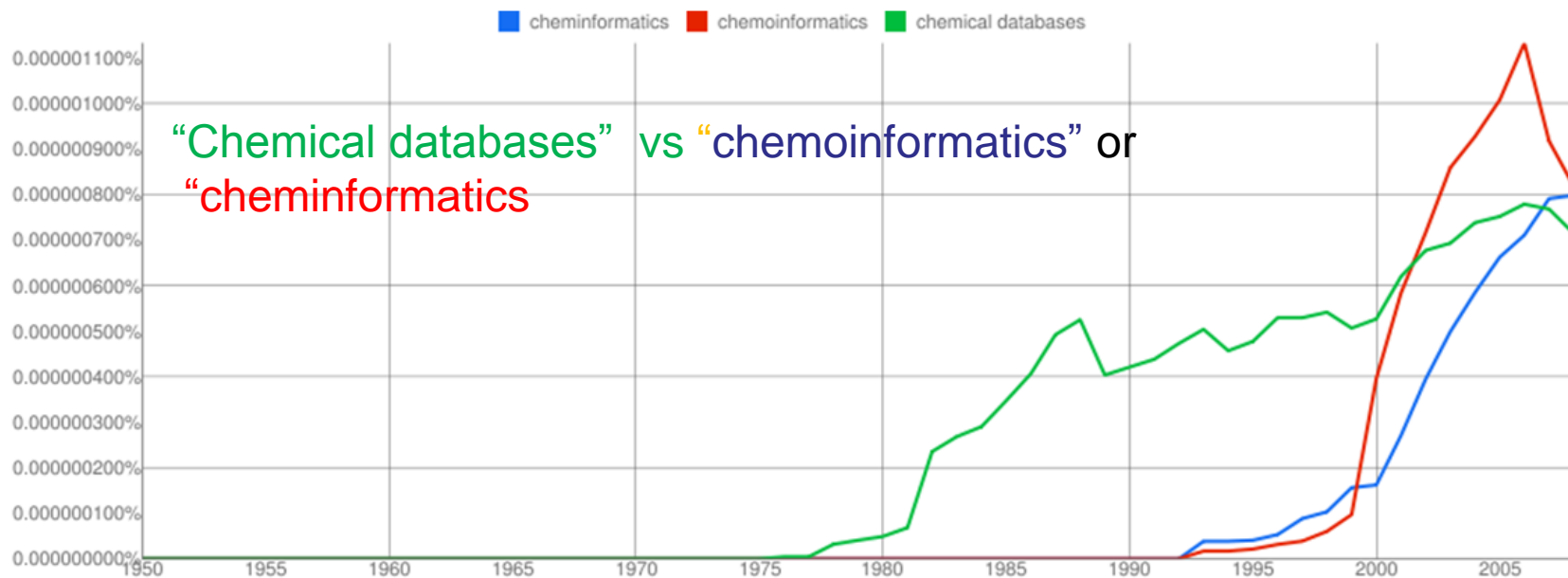
“Sequence data” vs. “bioinformatics”

Search in Google Books:

The importance of the DATA to enable any informatics-dependent discipline: *cheminformatics example*

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Graph these **case-sensitive** comma-separated phrases: between and from the corpus with smoothing of .



Search in Google Books:

The importance of the DATA to enable
any informatics-dependent discipline:
nanotoxicoinformatics example



- So far, three-four publications with enough data to build models
- Three-four computational modeling papers
- It is hard to collect and compile the data

Challenges of data integration: an example of Lung A549 cells.

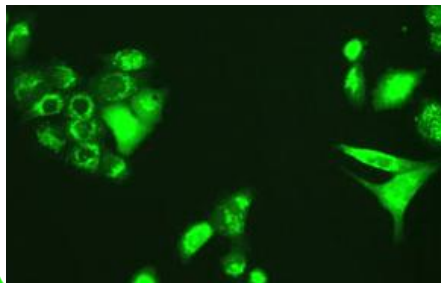
Pulskamp et al., Toxicol. Lett., 2007, 168, 58-74.

Several carbon MNPs (multi-walled, single-walled, carbon black, quartz) increased Reactive Oxygen Species (ROS) and decreased mitochondrial membrane potential in a dose- and time-dependent manner in rat macrophages and human **A549** lung cells.

Tahara et al., Int. J. Pharm., 2009, 382, 198-204.

The A549 cell uptake of chitosan-modified PLGA nanospheres is time-, temperature-, and concentration-dependent, regulated by clathrin-mediated endocytosis. Low cytotoxicity was reported for these modified, surface decorated nanospheres, suggesting them as preferable drug carriers for **A549** cells.

*Lung adenocarcinoma
A549 cells*



Liu et al., Nanotechnology, 2010, 21, 315106.

The authors demonstrated the efficiency for lung cancer treatment of nanodiamond NPs carrying paclitaxel on their surface: these NPs were found (i) to reduce the **A549** cell viability *in vitro* by inducing both mitotic arrest and apoptosis, and (ii) blocked the tumor growth in mice.

Deng et al., Nanotoxicology., 2010, 4, 186-195.
Foldbjerg et al., Arch. Toxicol., 2010, In Press.

PVP coated silver nanoparticles were reported to induce ROS and damage DNA in **A549** cells depending on their doses, as well as increase gap junctional intercellular communication.

Data depositories



Studies on MNP of different core structure, size, shape, and with various surface modifications have been reported but all published data are **diverse, non-searchable, and spread among numerous sources of information.**

- ➔ Lack of centralized data repository
- ➔ Limits our capability to develop predictive tools to assess nanotoxicity in advance of manufacturing
- ➔ Severely limits the design of novel nanomaterials that are environmentally benign and safe for human exposure

Specific Aim 1

SRC White Paper 2011 / Tropsha group



To compile, curate and organize a specialized database incorporating all existing information on MNP including their physical/chemical properties and associated biological data emerging both from SRC research teams and scientific literature.

Will facilitate research collaboration and data sharing between research teams;

Will enable computational modeling by providing larger sets of integrated and curated data;

Will highly benefit both experimentalists and modelers by enabling easily accessible, efficient data storage and in-depth analysis/modeling of all reported experiments.

Data sharing/storing format for nanomaterials



[Nanotechnology data sharing and standards](#) >

nano-TAB

nano-TAB is a tab-delimited spreadsheet type of format facilitating the submission and exchange of data pertaining to nanomaterials and their characterizations (physico-chemical, *in vitro*, and *in vivo*). nano-TAB is based on existing standards developed by the European Bioinformatics Institute (EBI) and the Investigation/Study/Assay (ISA-TAB) file format, which represents a variety of assays and technology types. The nano-TAB specification leverages ISA-TAB files describing investigations, studies, and assays and provides extensions to support nanomaterial structural information and concepts on nanotechnology assay measurements defined in the NanoParticle Ontology (NPO).

The goals of nano-TAB are to:

- Enable the submission and exchange of nanomaterials to/from nanotechnology resources
- Empower organizations to adopt standards for representing data in nanotechnology publications, and
- Provide researchers with guidelines for representing nanomaterials and characterizations to achieve cross-material comparison

The nano-TAB project is a sub-group of the caBIG Nano WG and has been assisted in clo Representation (IR) Working Group (WG). The nano-TAB project is a collaborative effort w registered [ASTM Work Item WK28974](#). Links to key nano-TAB artifacts are provided below

- [nano-TAB Overview Presentation](#) (this is the best starting place to learn about
- [nano-TAB Specification \[DRAFT\]](#)
- [nano-TAB Template](#)
- [nano-TAB Template Glossary](#)
- nano-TAB Example Files:
 - [NCL Dendrimer MRI Contrast Agent](#)
 - [NBI AU Nanoparticle](#)
- nano-ML (nano-TAB XML Representation)
 - [nano-ML XML Schema](#)
 - [nano-ML Example File](#)

nano-TAB project meeting presentations, minutes and other files on the nano-TAB develop http://gforge.nci.nih.gov/docman/index.php?group_id=69&selected_doc_group_id=5653&la

Sample Identifiers Protocol Reference

Sample Material Name	Protocol Ref	Parameter Value (Instrument)	Parameter Value (pt of use)	Parameter Value (MAGI concentration)
NCL-0	Hydrodynamic Size Distribution via Dynamic Light Scattering	2000	2000	7.4
NCL-0	Hydrodynamic Size Distribution via Dynamic Light Scattering	2000	2000	7.4
NCL-0	Hydrodynamic Size Distribution via Dynamic Light Scattering	2000	2000	7.4
NCL-0	Hydrodynamic Size Distribution via Dynamic Light Scattering	2000	2000	7.4
NCL-0	Hydrodynamic Size Distribution via Dynamic Light Scattering	2000	2000	7.4
NCL-0	Hydrodynamic Size Distribution via Dynamic Light Scattering	2000	2000	7.4
NCL-0	Hydrodynamic Size Distribution via Dynamic Light Scattering	2000	2000	7.4

Assay Name Study Factors

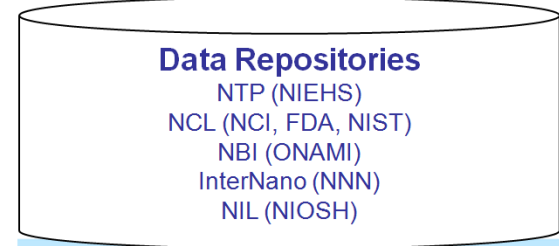
Performer	Date	Assay Name	Factor Value (Temperature)	Unit	Term Source	Term Accession	Factor Value (media solvent)
Amil Path	2010-05-12	Size by DLS	25	degrees	UD		celline
Amil Path	2010-05-12	Size by DLS	25	degrees	UD		PS
Amil Path	2010-05-12	Size by DLS	25	degrees	UD		celline
Amil Path	2010-05-12	Size by DLS	25	degrees	UD		celline
Amil Path	2010-05-12	Size by DLS	25	degrees	UD		PS
Amil Path	2010-05-12	Size by DLS	25	degrees	UD		celline
Amil Path	2010-05-12	Size by DLS	25	degrees	UD		PS
Amil Path	2010-05-12	Size by DLS	25	degrees	UD		PS

Assay Measurements Assay Files

Measurement Value (Z-avg (nm))	Measurement Value (Peak size (nm))	Measurement Value (pDI)	Image File	Derived Data File
8.2	8.4	0.241	0_123_distribution.jpg	nci_20.xls
8.8	8.0	0.200	0_200_distribution.jpg	nci_22.xls
8.8	8.2	0.214	0_214_distribution.jpg	nci_23.xls
7.9	8.1	0.285	0_285_distribution.jpg	nci_24.xls
7.4	8.3	0.210	0_210_distribution.jpg	nci_25.xls
8.4	8.2	0.243	0_243_distribution.jpg	nci_26.xls
8.8	8.4	0.210	0_210_distribution.jpg	nci_27.xls

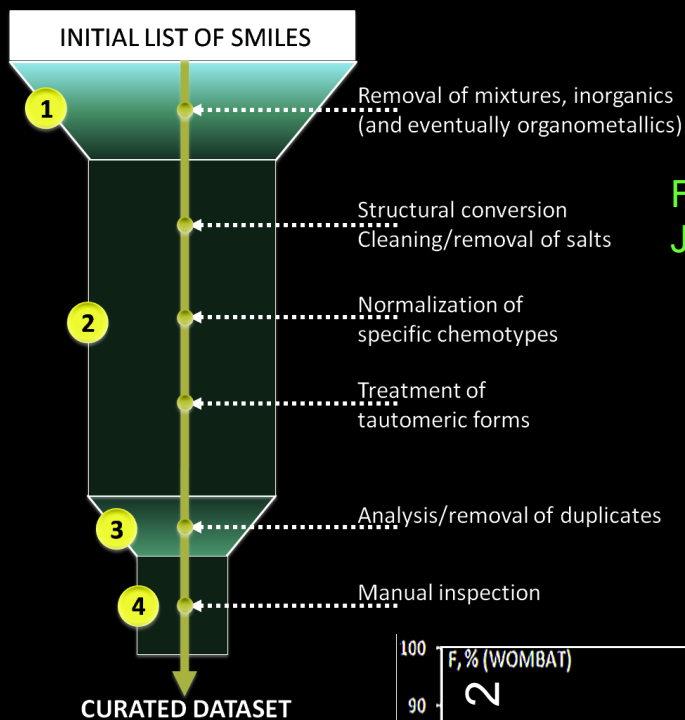
STANDARDIZED

STANDARDIZED




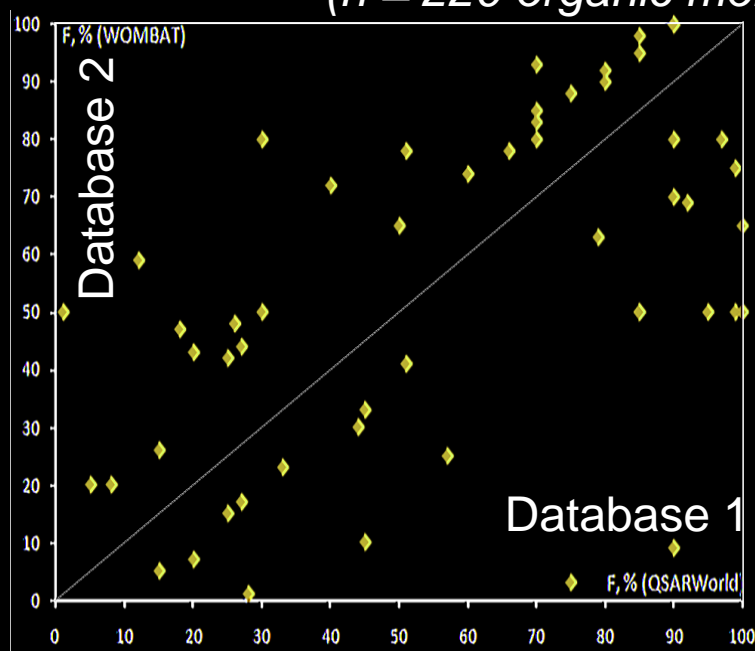
<https://sites.google.com/site/cabignanowg/data-sharing-and-nanotechnology-standards/nanotab>

Solving chemical and biological data curation issues



Fourches, D.; Muratov, E.; Tropsha, A.
J. Chem. Inf. Model. 2010, 50, 1189-1204.

Bioavailability data
(*n* = 220 organic molecules)



**Similar
Issues
With
Nanoparticles**

Outline: From data to models to computer-aided design



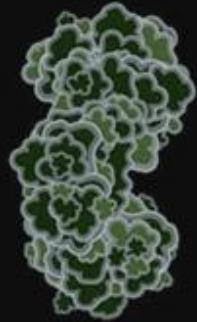
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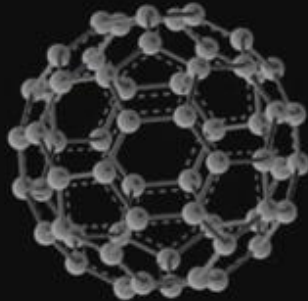
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Difficulties in Modeling of Nanomaterials



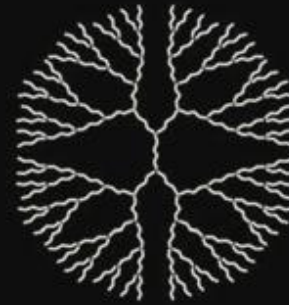
Diesel Exhaust Particles



Fullerene



Nanotubes



Dendrimers



Quantum Dots

← Incidental Nanoparticles

→ Engineered Nanoparticles

S. Stern and S. McNeil, *Toxicological Sciences*, 101(1), 4-21, 2008.


- NP structures are **very diverse** → a real challenge to develop quantitative parameters (**descriptors**) of MNPs.
- Systematic physico-chemical, geometrical, structural and biological studies of NPs are nearly absent.
- **Computational modeling of nanoparticles is only beginning to emerge; best if done in collaboration with experimental scientists.**

Simplest view of QNAR



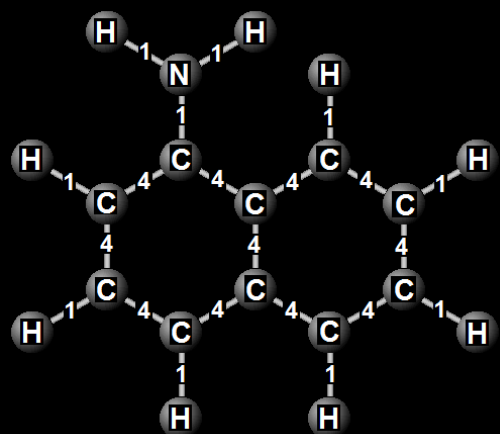
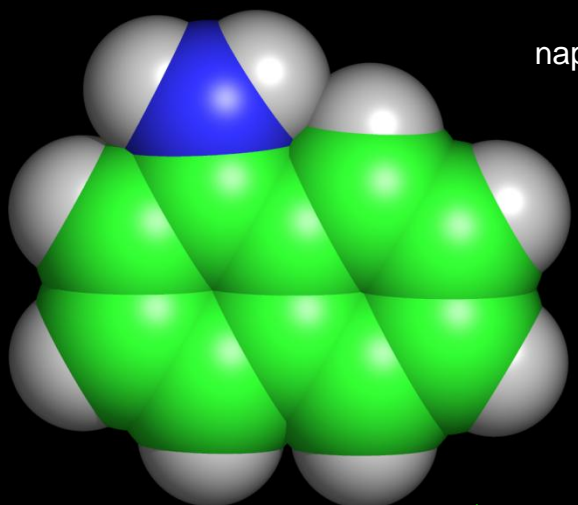
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progression

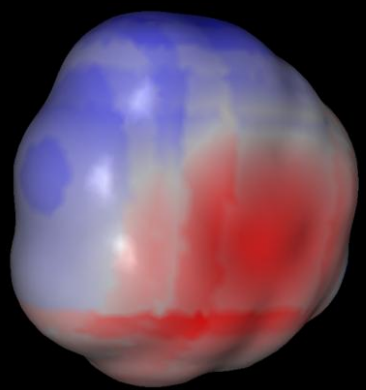
- Experimental Data
 - Structure
 - Activity
 - Validated models of data
 - Descriptors
 - Statistical/machine learning techniques
 - Imputed data
 - Experimentally confirmed predictions
 - Reliable models to enable decision support (both in research and regulations)
- = pain*
- 
- = gain*

Structure representation in cheminformatics

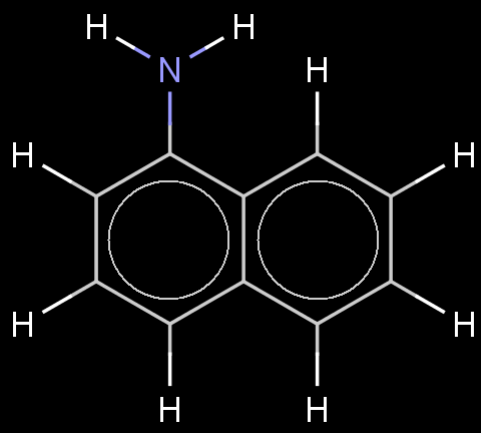
naphtalen-1-amine



Viewed by computers



Viewed by another molecule



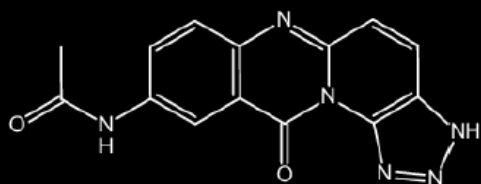
Viewed by chemists

Compounds are represented by a matrix of molecular descriptors



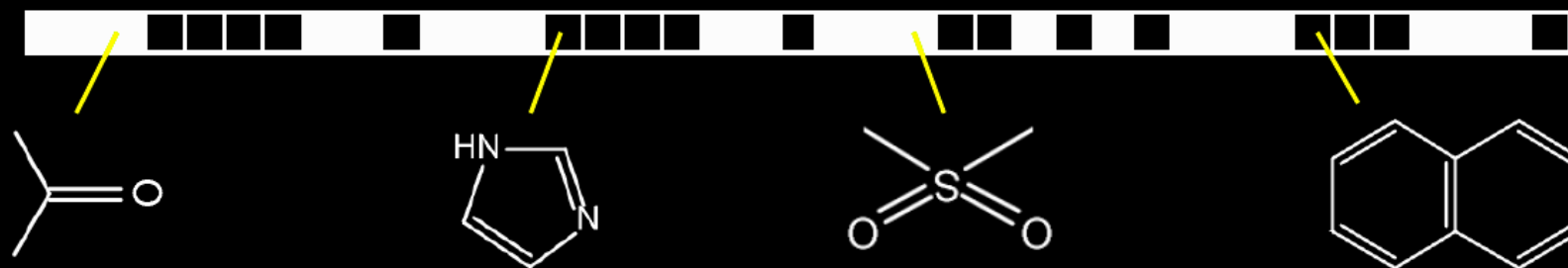
Samples (Compounds)	Variables (descriptors)			
	X_1	X_2	...	X_m
1	X_{11}	X_{12}	...	X_{1m}
2	X_{21}	X_{22}	...	X_{2m}
...
n	X_{n1}	X_{n2}	...	X_{nm}

Molecular fingerprints - bit string encodings of structural features and/or calculated molecular properties.

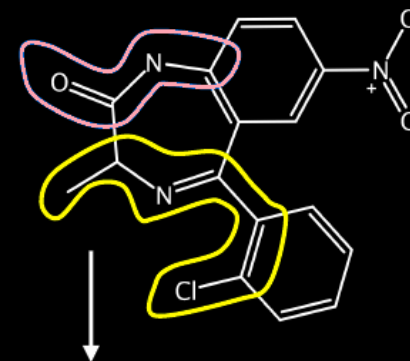


molecular fingerprint

- **2D Fragment-based**, keyed fingerprints: each bit position monitors the presence or absence of structural fragments
MACCS (166 bits), **BCI** (e.g. 1,052 bits)



- **2D Hashed designs:**
Map different features (e.g. connectivity pathways) to overlapping bit segments
Daylight (usually 2,048 bits)



Pathways: O=CNC, ..., CCN=CC=CCl

Similarity Search

Similarity searching using fingerprint representations of molecules is one of the most widely used approaches for chemical database mining: it assumes that **similar compounds possess similar biological activities.**

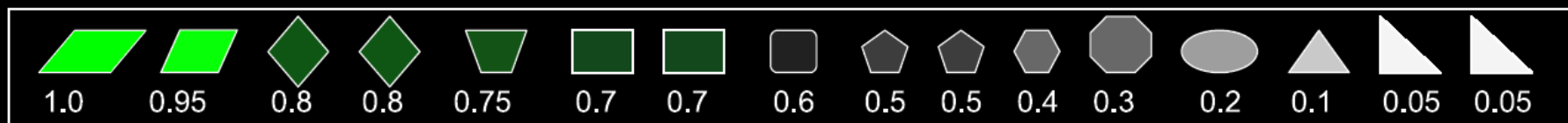


similarity assessment

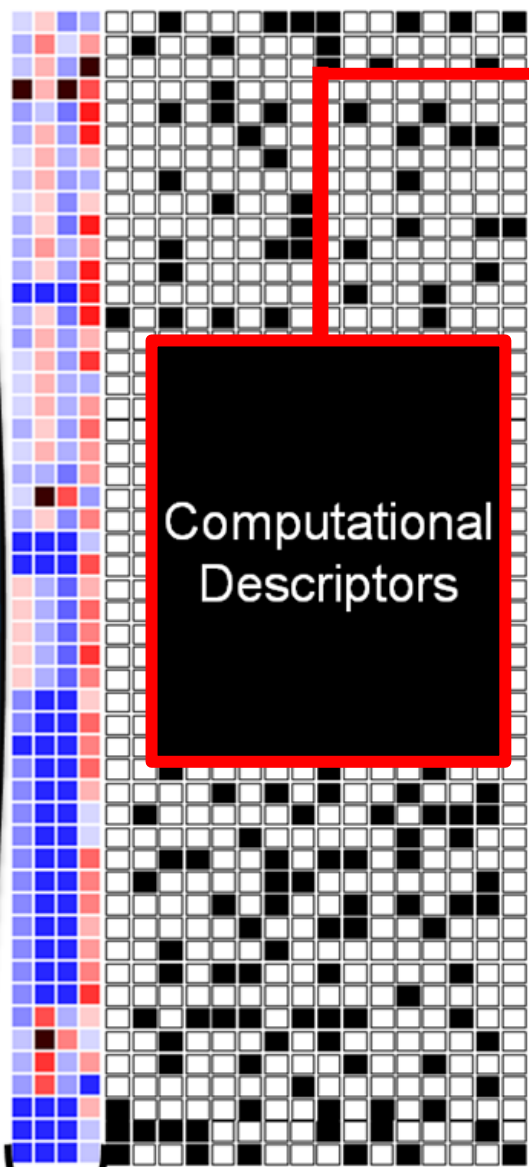
Tanimoto Coefficient

$$Tc(X_A, X_R) = \frac{c}{a + r - c}$$

ranked list of database molecules



NANOPARTICLES



Computational Descriptors

DESCRIPTORS

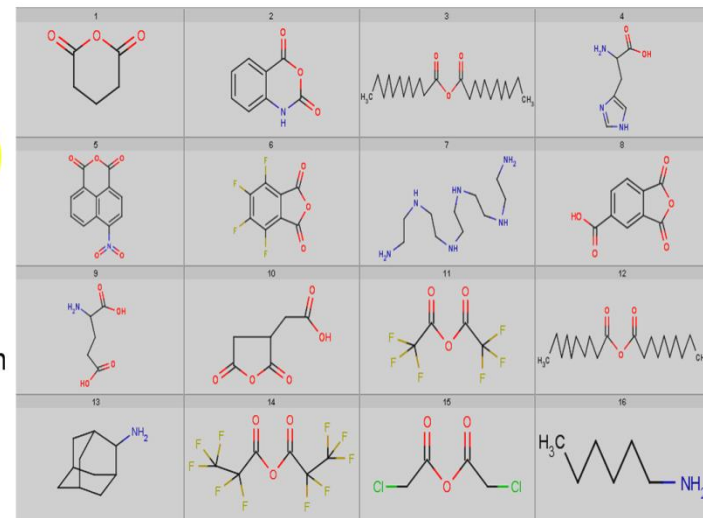
Experimental properties

ALL PARTICLES HAVE THE SAME CORE BUT DIFFERENT SURFACE MODIFIERS



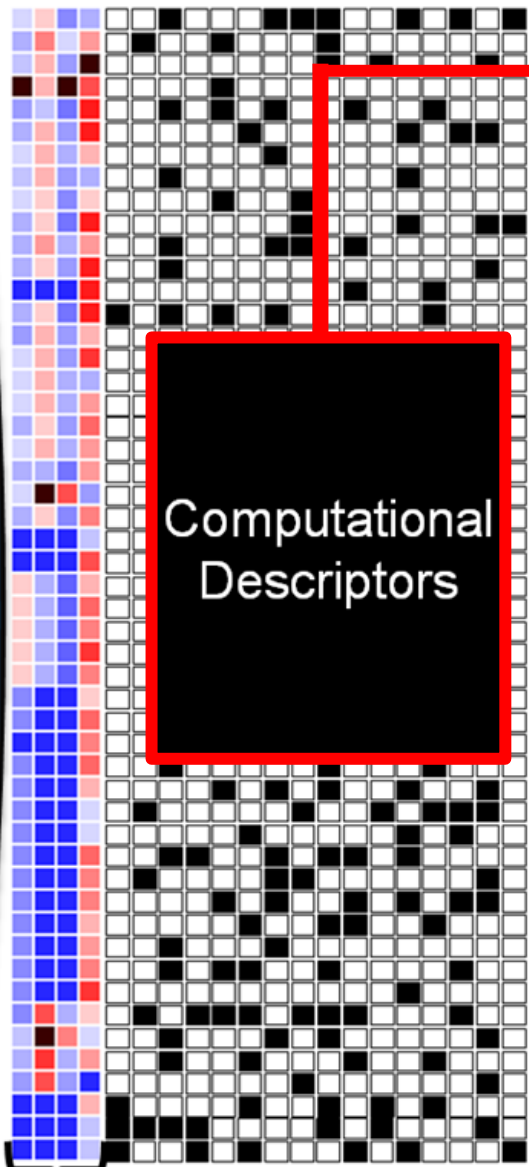
▶ FITC (fluorescein isothiocyanate)

Small organic compounds



Classical molecular descriptors (e.g., Dragon, MOE, SiRMS) can be computed for a single molecule that represents the surface of a particular nanoparticle.

NANOPARTICLES



DESCRIPTORS

Computational Descriptors

Experimental properties

ALL PARTICLES HAVE DIFFERENT CORES/ARCHITECTURES

MNP	CLIO	PNP	MION	QD	Feridex IV	Ferrum Hausmann
#. particle	23	19	4	3	1	1

Shaw et al., PNAS, 2008, 105, 7387-7392

If no available three-dimensional structures, only constitutional descriptors (e.g., number of metal atoms, presence/absence of coated dextran) are computationally accessible.

Need of developing new descriptors

Development of Quantum-Mechanics based fingerprints for thousands of nanomaterials in collaboration with Dr. Stefano Curtarolo (Duke University)

Outline: From data to models to computer-aided design



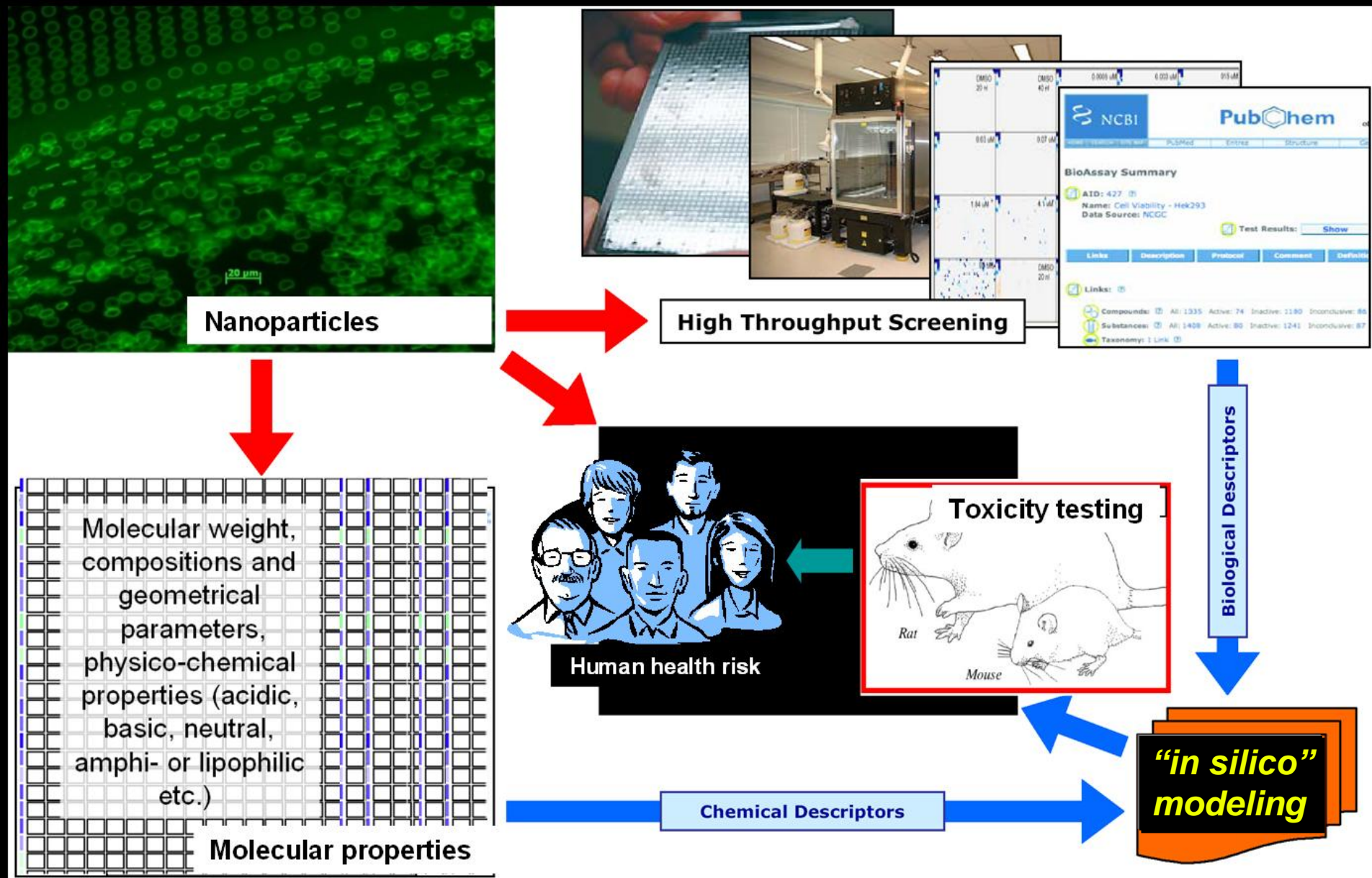
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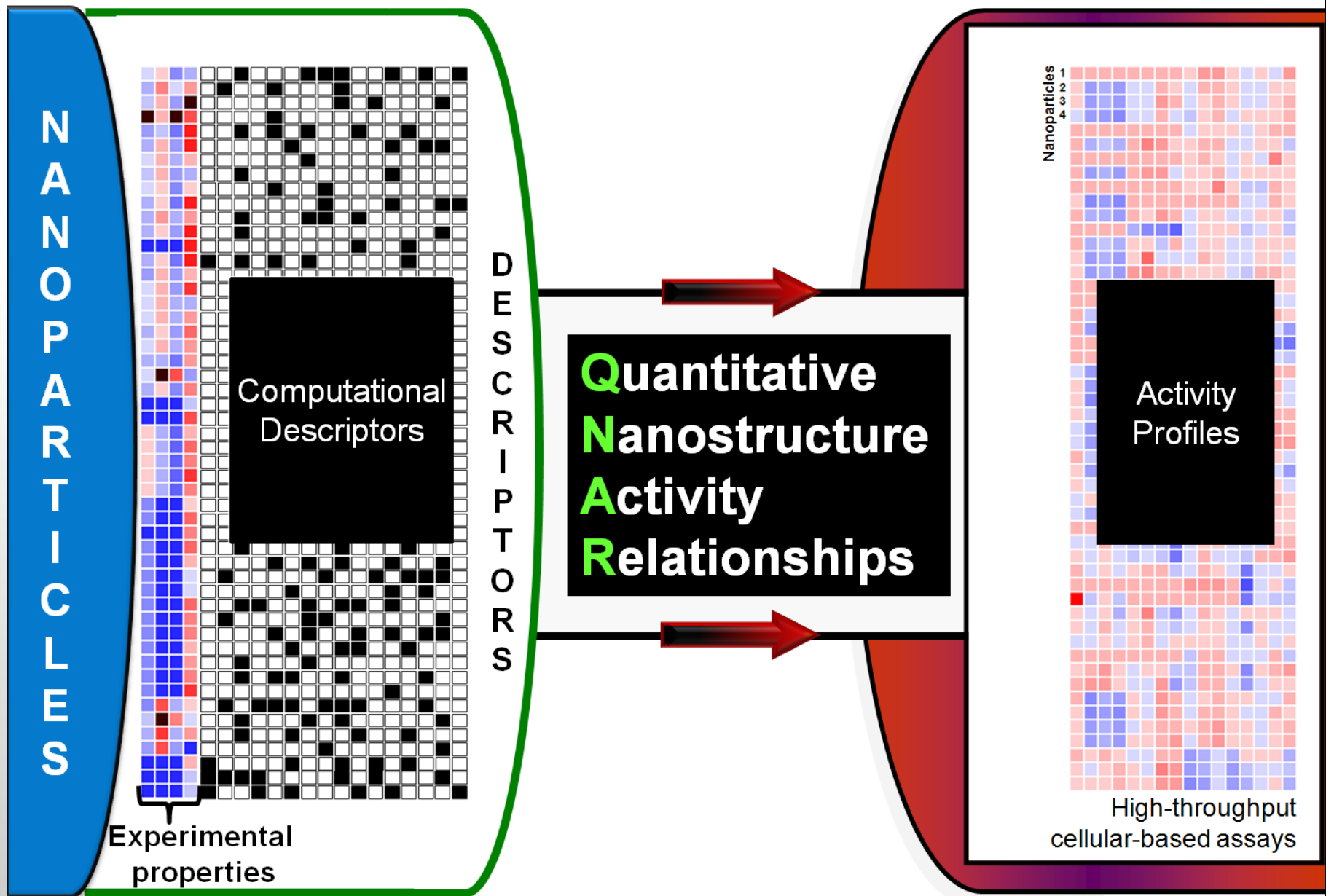
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Workflow for MNP risk assessment





2010 Oct 26;4(10): 5703-12.

Quantitative Nanostructure—Activity Relationship Modeling

Denis Fourches,[†] Dongqiuye Pu,[†] Carlos Tassa,[‡] Ralph Weissleder,[‡] Stanley Y. Shaw,[‡] Russell J. Mumper,[§] and Alexander Tropsha^{†,*}

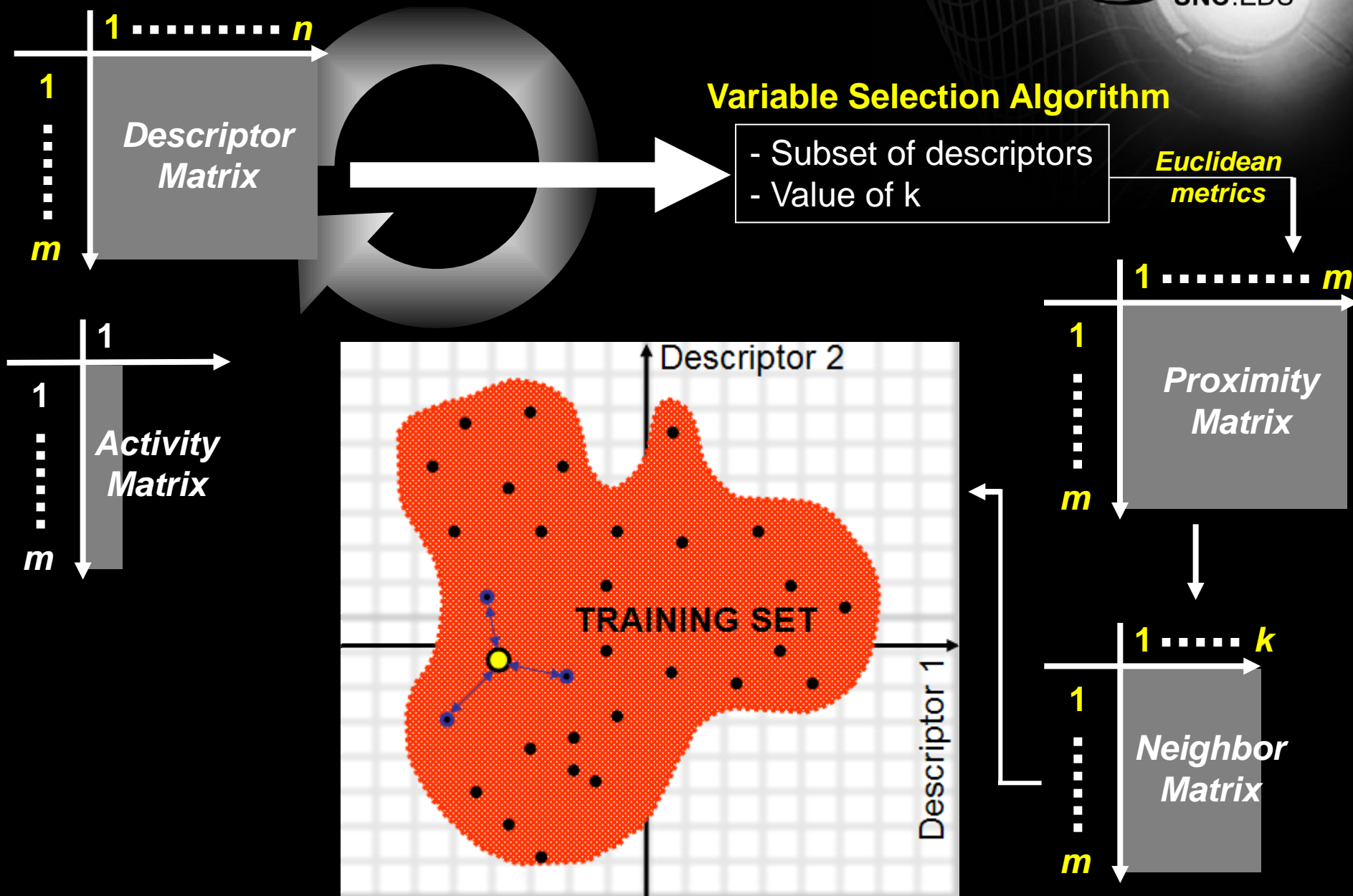
[†]Laboratory of Molecular Modeling, UNC Eshelman School of Pharmacy, University of North Carolina, Chapel Hill, North Carolina 27599, [‡]Center for Systems Biology, Massachusetts General Hospital, Boston, Massachusetts 02114, and [§]Center for Nanotechnology in Drug Delivery, UNC Eshelman School of Pharmacy, University of North Carolina, Chapel Hill, North Carolina 27599

More than 1000 manufacturer-identified, nanotechnology-based consumer products are currently available on the market (The Woodrow Wilson International Center for Scholars, 2010). A growing fraction of them represent green products intended to achieve efficient and less polluting energy sources.¹ However, some manufactured nanoparticles (MNPs) intended for industrial applications may cause toxic effects in humans,^{2–4} and public concern about the safety of MNPs is increasing.⁵ Understanding biological ef-

ARTICLE

ABSTRACT Evaluation of biological effects, both desired and undesired, caused by manufactured nanoparticles (MNPs) is of critical importance for nanotechnology. Experimental studies, especially toxicological, are time-consuming, costly, and often impractical, calling for the development of efficient computational approaches capable of predicting biological effects of MNPs. To this end, we have investigated the potential of cheminformatics methods such as quantitative structure—activity relationship (QSAR) modeling to establish statistically significant relationships between measured biological activity profiles of MNPs and their physical, chemical, and geometrical properties, either measured experimentally or computed from the structure of MNPs. To reflect the context of the study, we termed our approach quantitative nanostructure—activity relationship (QNAR) modeling. We have employed two representative sets of MNPs studied recently using *in vitro* cell-based assays: (i) 51 various MNPs with diverse metal cores (*Proc. Natl. Acad. Sci.* 2008, 105, 7387–7392) and (ii) 109 MNPs

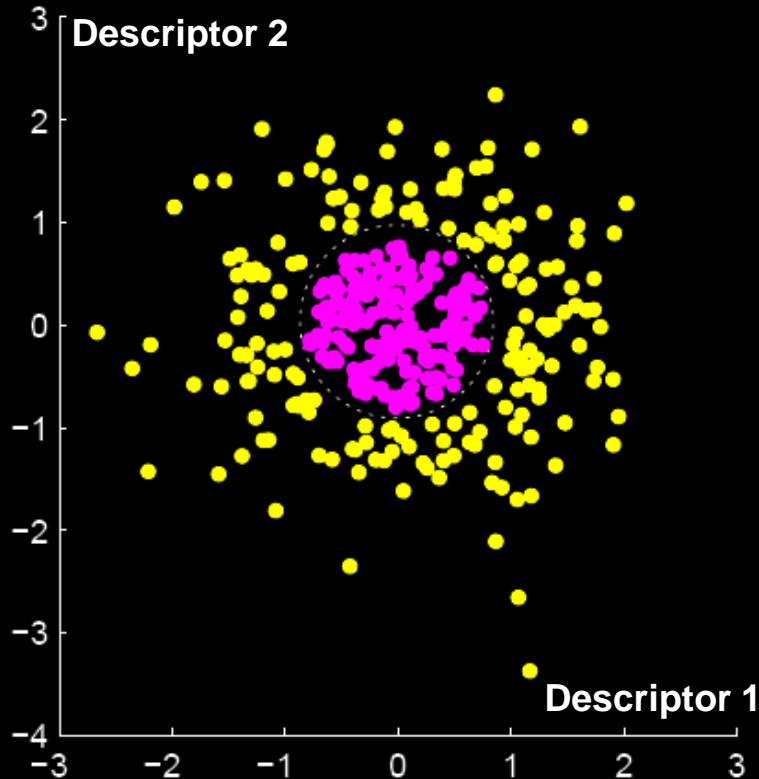
MML - k Nearest Neighbors (kNN) method



Support Vector Machine (SVM)

Introduced by Vapnik (1995), the SVM approach identifies the best linear separation between two classes of data. In a multidimensional descriptor space, such separation is realized by a hyperplane leading to the best linear segregation between data in the feature space.

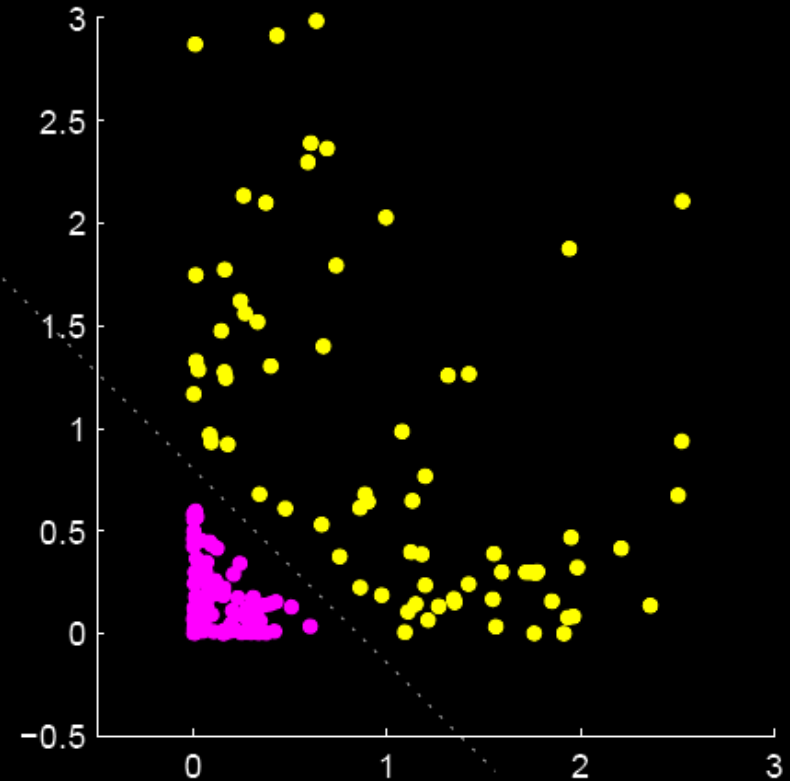
What is the feature space ?



Descriptor space : no linear separation between data points.

Kernel Function
(Ex: x^2, y^2)

→
←

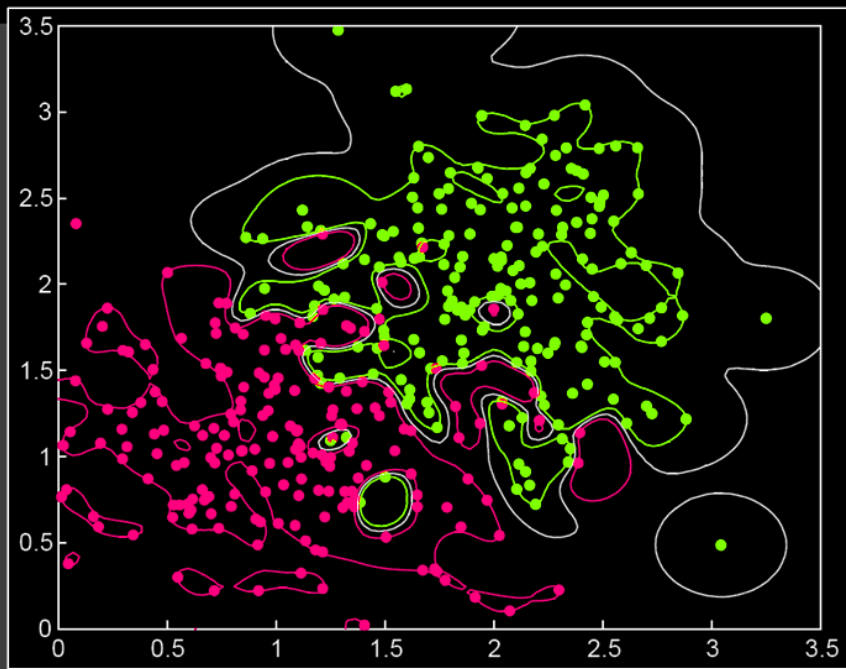


Feature space : linear separation exists.

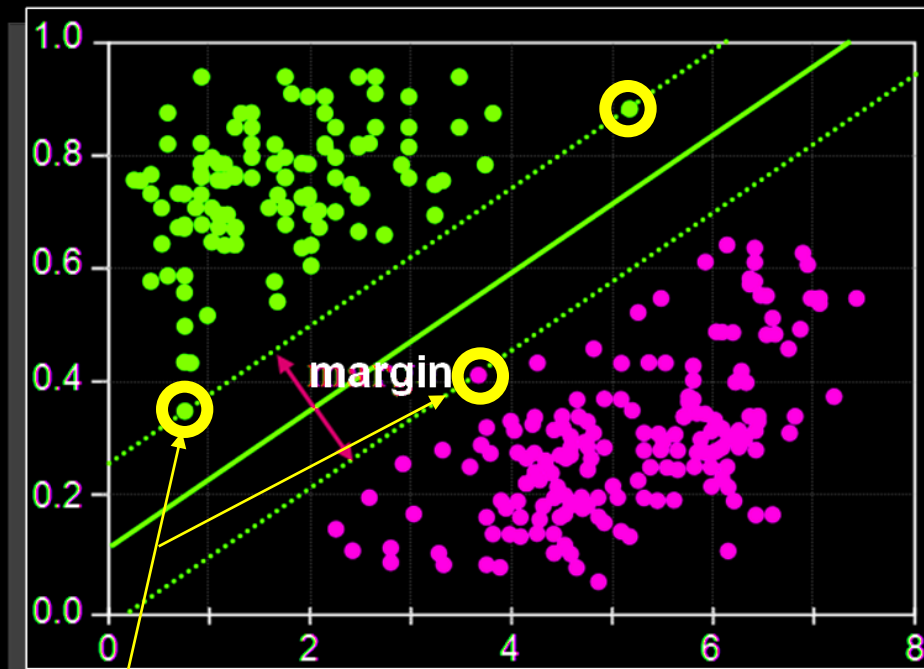
Support Vector Machine (SVM)

The SVM algorithm tends to maximize the margin around the hyperplane separating the two classes of compounds. Different kernel functions and parameters have to be optimized (grid search) in order to identify the best models.

Descriptor space

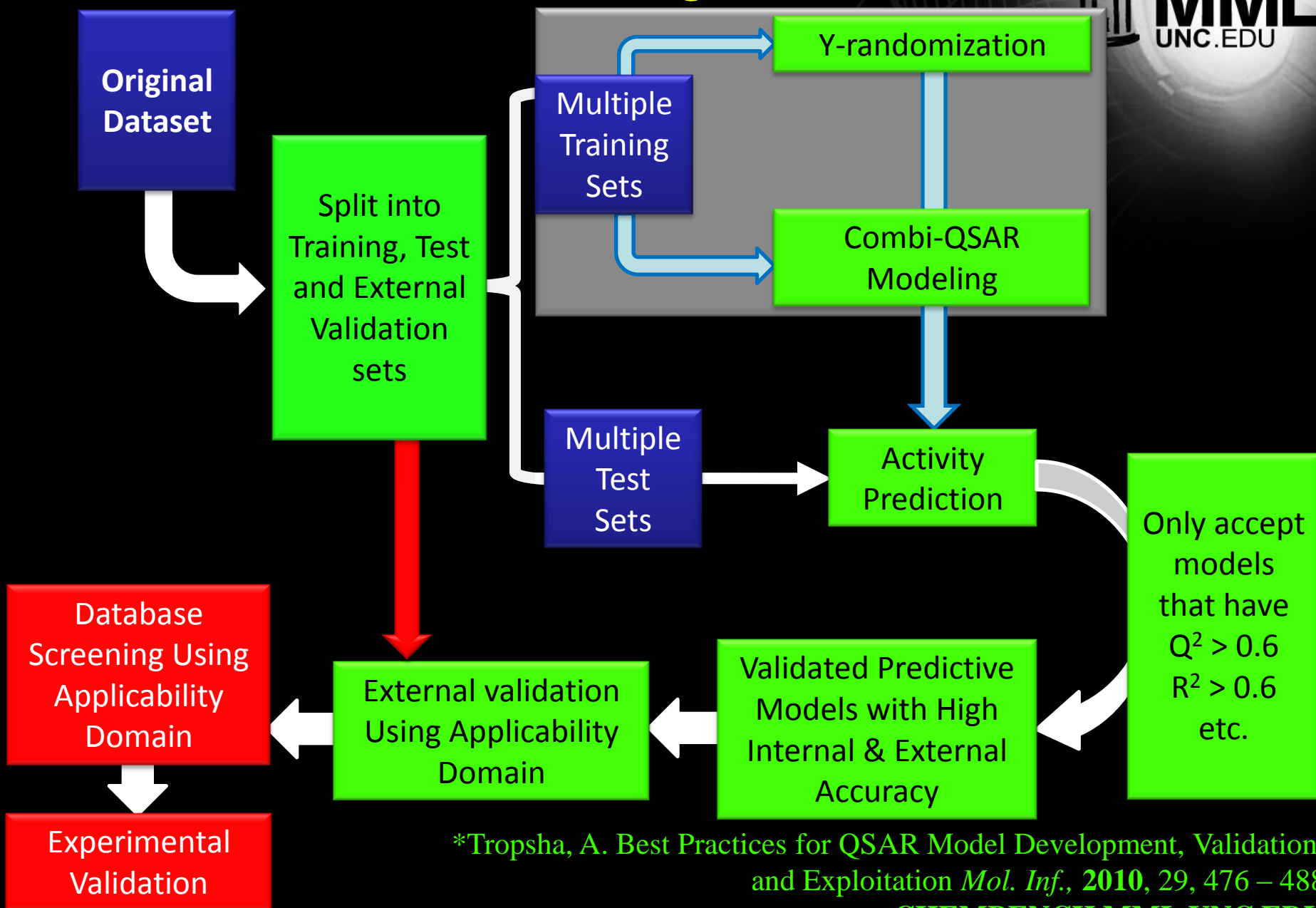


Feature space



Support vectors

Predictive QSAR Modeling Workflow*



*Tropsha, A. Best Practices for QSAR Model Development, Validation, and Exploitation *Mol. Inf.*, **2010**, 29, 476 – 488

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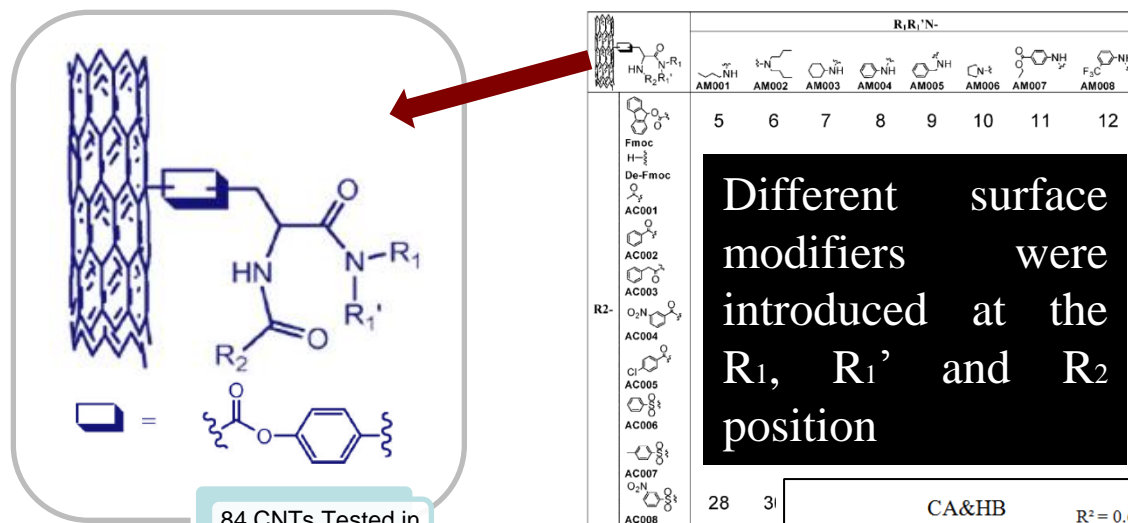
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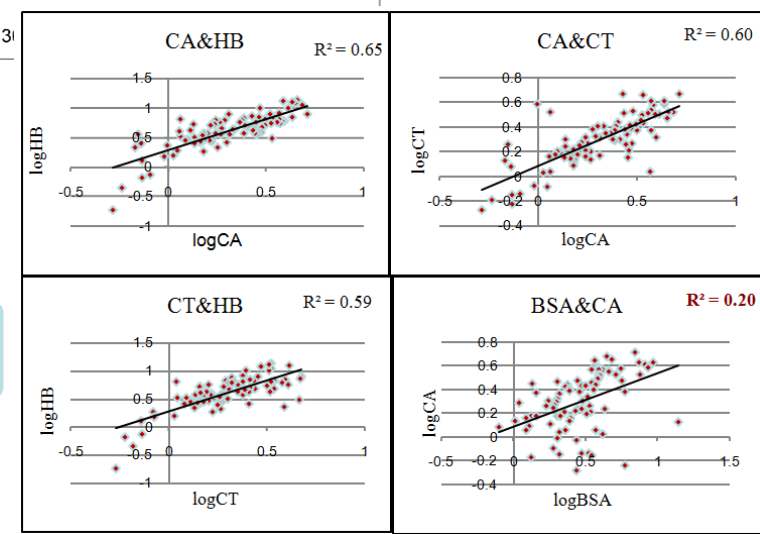
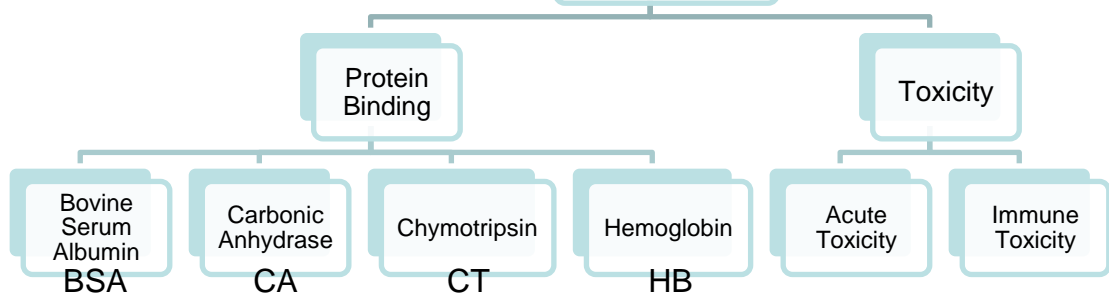
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Case Study 3: Modeling of NPs for Protein Binding

In 2008, Zhou et al* published *in vitro* protein binding, acute toxicity and immune toxicity assays for 84 Carbon NanoTubes (CNTs) decorated with different surface modifiers.



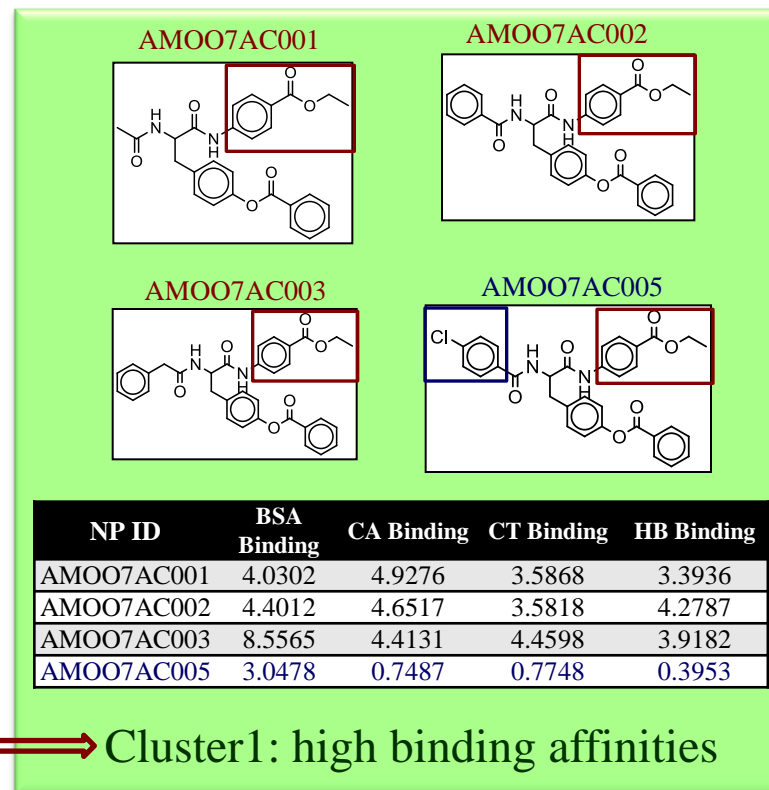
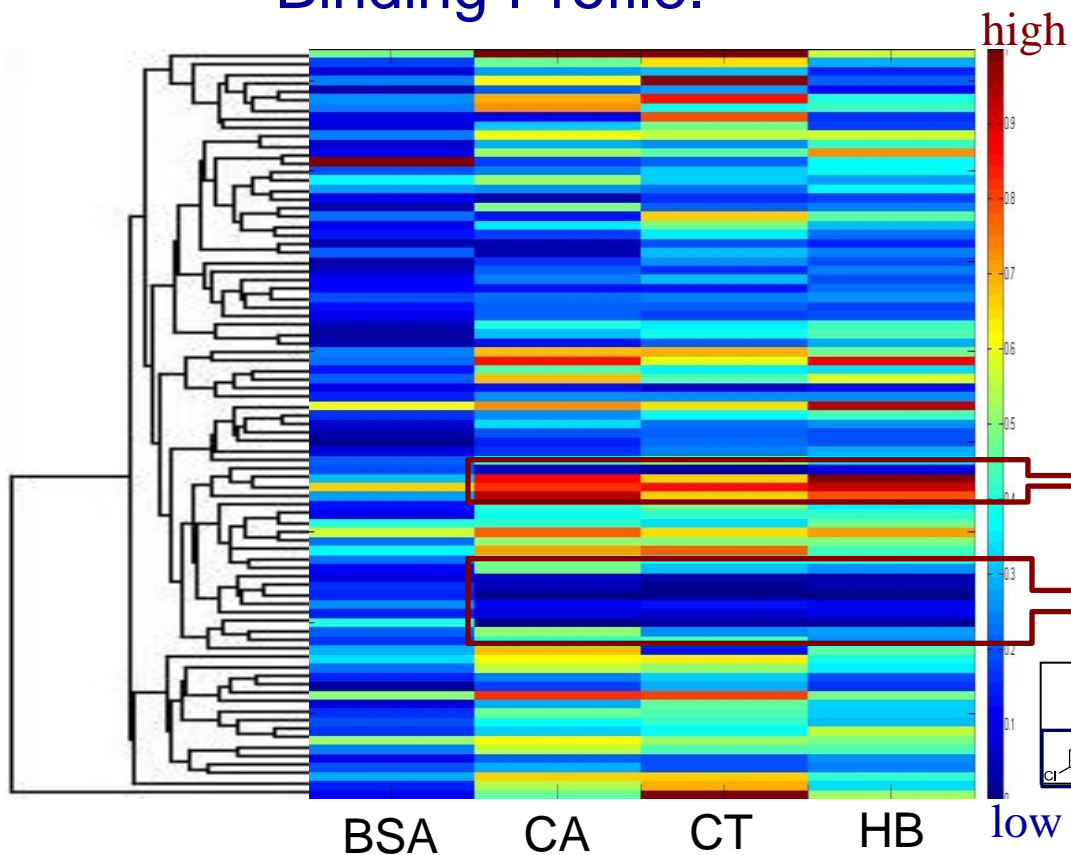
84 CNTs Tested in Two Different Types of Assays



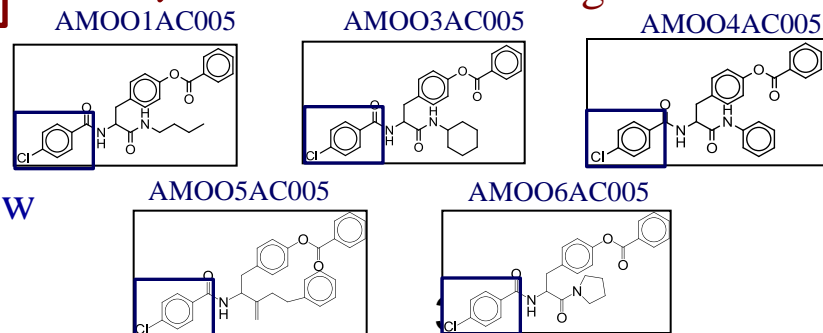
*Zhou et al. *Nano Lett.*, Vol. 8, No. 3, 2008

Case Study 3: Binding profiles sorted according to non-supervised hierarchical clustering of 84 NPs using chemical descriptors

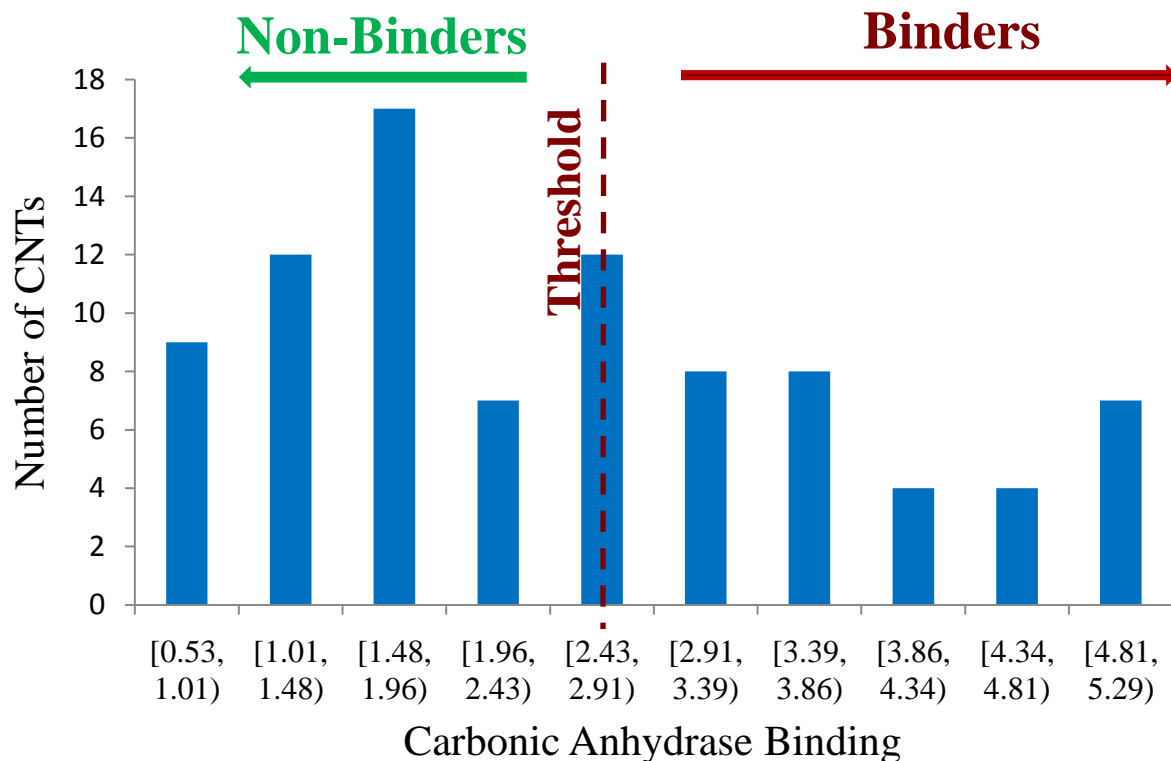
Clustering Uncovers Common Fragments with Distinct Protein Binding Profile.



Cluster 2: low binding affinities



Case Study 3: QNAR Modeling of Carbonic Anhydrase Binding



Each CNT is represented by a single copy of its surface molecule.

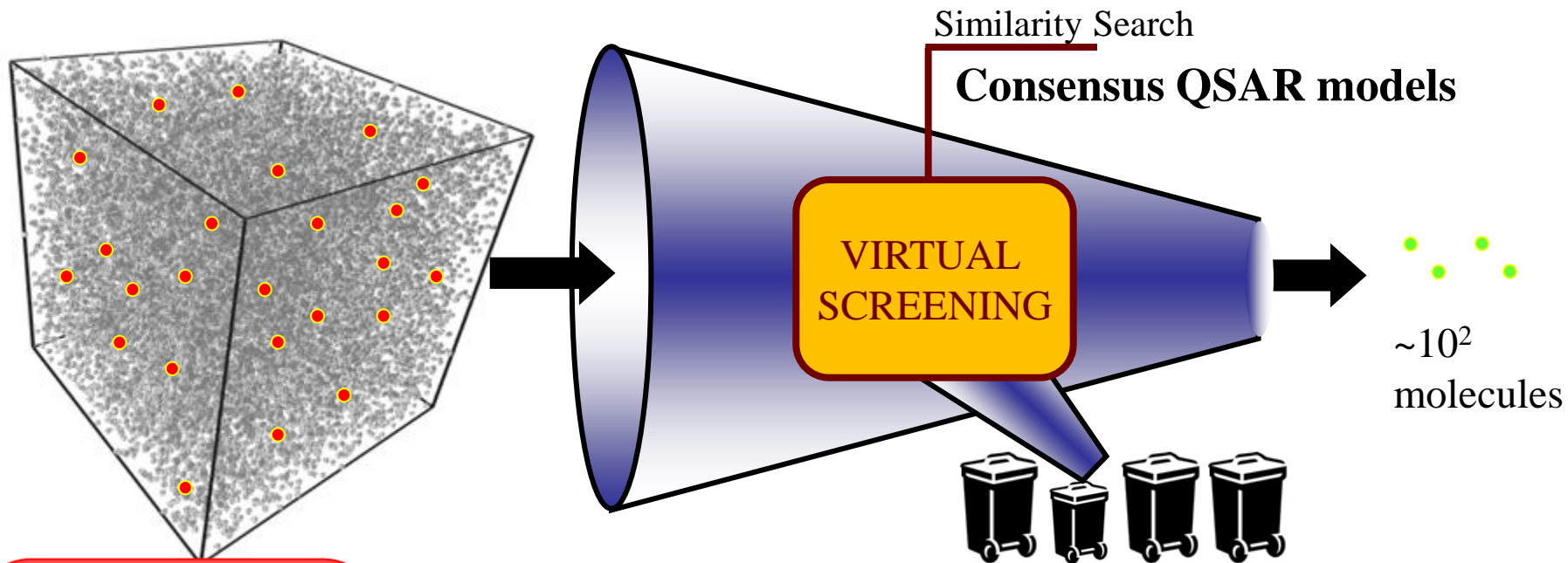
Consensus modeling approach combining different machine learning methods (k Nearest Neighbors, Support Vector Machines and Random Forest) and different types of chemical descriptors (Dragon and MOE).

Case study 3: QNAR Modeling of CA Binding

		kNN-Dragon	SVM-Dragon	RF-Dragon	kNN-MOE	SVM-MOE	RF-MOE
F1	Sens.	0.70	0.70	0.70	0.70	0.70	0.70
	Spec.	0.83	0.83	0.83	0.83	0.67	0.83
	Accr.	0.75	0.75	0.75	0.75	0.69	0.75
F2	Sens.	0.80	0.60	0.80	0.80	0.70	0.80
	Spec.	1.00	1.00	1.00	1.00	0.67	1.00
	Accr.	0.88	0.75	0.88	0.88	0.69	0.88
F3	Sens.	0.88	0.75	0.75	0.50	0.63	0.75
	Spec.	0.63	0.44	0.75	0.63	0.50	0.50
	Accr.	0.75	0.63	0.75	0.56	0.56	0.63
F4	Sens.	0.86	0.86	0.86	0.86	0.86	0.43
	Spec.	0.67	0.56	0.67	0.67	0.44	0.67
	Accr.	0.75	0.69	0.75	0.75	0.63	0.56
F5	Sens.	0.63	0.63	0.63	0.63	0.50	0.63
	Spec.	0.64	0.64	0.55	0.45	0.64	0.55
	Accr.	0.63	0.63	0.58	0.53	0.58	0.58
Total	Sens.	0.77	0.70	0.74	0.70	0.67	0.67
	Spec.	0.73	0.68	0.73	0.68	0.58	0.68
	Accr.	0.75	0.69	0.73	0.69	0.63	0.67

Case Study 3: Computer-aided design of novel carbon nanotubes with desired biological properties

(in collaboration with Dr. Bing Yan, St. Jude Children's Research Hospital)



240,000 *in silico* designed small molecules which are considered attachable to CNTs

Similarity Search

462 molecules

QNAR Predictions

CA non-binders

110 molecules

Non-toxic

189 molecules

Experimental Validation

Experimental Validation (Toxicity assay)

Hits that were predicted as **non-toxic**

Cell Viability (%) = $100 \times \text{treatment} / \text{control}$ (percentage)

ID	Cell Viability (%) = $100 \times \text{treatment} / \text{control}$ (percentage)				Average	STDEV
	Rep1	Rep2	Rep3	Rep4		
II-1 (1831)	55	53	60	63	58	5
II-2 (48660)	57	62	62	63	61	2

All rationally prioritized, synthesized, and tested CNTs predicted as non-toxic were confirmed experimentally.

II-6 (153907)	79	65	61	56	65	10
II-7 (153852)	73	72	66	62	68	6
II-8 (39260)	67	67	70	82	72	7
II-9 (13860)	72	67	66	67	68	3
II-10 (48636)	54	53	63	65	59	6

Experimental Validation (Toxicity assay)

Hits that were predicted as toxic

Cell Viability (%) = $100 \times \text{treatment} / \text{control}$ (percentage)

ID	Cell Viability (%) = $100 \times \text{treatment} / \text{control}$ (percentage)				Average	STDEV
	Rep1	Rep2	Rep3	Rep4		
II-11 (170243)	38	29	38	52	39	9
II-12 (170217)	49	50	38	58	49	8

6 out of 10 rationally prioritized, synthesized, and tested CNTs predicted as toxic were confirmed experimentally

II-16 (154018)	44	49	47	24	41	11
II-17 (4218)	44	51	54	56	51	5
II-18 (135817)	41	44	53	60	49	9
II-19 (120618)	47	43	66	62	55	11
II-20 (135018)	40	43	59	60	50	10

Conclusions

- Our results demonstrate that QNAR models can successfully predict the biological effects of MNPs from their descriptors either experimentally measured or calculated.
 - Selected nanotubes decorated by the ligands identified with the help of QNAR models were experimentally synthesized and successfully validated. This study reports the first case of a rational design of carbon nanotubes possessing desired properties.
 - QNAR models can be used to design new MNPs with appropriate bioactivity and safety profiles.
-

Needs



- *(side note: the technology to build models is in place: 50 years of QSAR!)*
- **Sufficiently large datasets**
Both the core and the surface are varied systematically to dissect their relative effects on biology.
- **NP-specific descriptors**
 - easy for surface modifiers (unless there are non-linear core/surface modifier effects);
 - non-existent for the core (except maybe, QM calculations and MD-simulations derived?)
 - QSPR should precede QNAR
- **Joint (e.g., virtual collaboratory) projects between computational and experimental teams**



More questions and challenges than answers and solutions (*good for science!*)

- Relationships between *in vitro* and *in vivo* responses?
 - Interplay between the structure of the core and that of surface modifiers as it affects toxicity?
 - Greater understanding of the relationship between structure and physical properties of NPs (to impute the latter)
 - Much greater effort is needed to generate designed datasets for focused QNAR investigations.
 - Urgent need to develop ontology and integrated databases of structure and physical and biological properties of NPs
-

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